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Life cycle sustainability decision-support framework for ranking of hydrogen production pathways under uncertainties: An interval multi-criteria decision making approach

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Abstract: Hydrogen as a clean energy carrier has been recognized as a promising alternative for emissions mitigation and environmental protection. Life cycle sustainability assessment (LCSA) of hydrogen can help the decision-makers/stakeholders to select the most sustainable pathway for hydrogen production in life cycle perspective among several alternatives. This study aims at developing a life cycle sustainability decision-support framework for ranking hydrogen production pathways by combining LCSA and interval multi-criteria decision making (MCDM) method. A novel interval MCDM method which can handle interval numbers in the decision-making matrix was developed by combining the improved decision-making trial and evaluation laboratory (DEMATEL) and interval evaluation based on distance from average solution (EDAS). Four pathways for hydrogen production, including coal gasification (CG), stream reforming of methane (SMR), biomass gasification (BG), and wind turbine electrolysis (WEL), have been studied by the proposed method. BG was recognized as the most sustainable one among these four scenarios, following by SMR, WEL, and CG in the descending order. Sensitivity analysis was carried out to investigate the effects of the weights of the indicators for sustainability assessment on the final ranking. The interval sum weighted method (ISWM) and interval TOPSIS method were also employed to validate the results determined by the proposed interval EDAS in this study and the results reveal that BG was recognized as the most sustainable scenario by all these three methods.

Keywords: life cycle sustainability assessment; hydrogen production; multi-criteria decision making; interval decision making; uncertainties

1. Introduction

Hydrogen as an alternative energy carrier for transportation has attracted more and more attentions, because there is no emission during its oxidation (Ren *et al*., 2015a; Ren *et al*., 2015b). There are various ways for hydrogen production, i.e. coal gasification, stream reforming of methane, biomass gasification, and water electrolysis. Although there is zero emission during the utilization stage of hydrogen, there are also some negative impacts on the environmental during its production stage (Bhandari *et al*., 2014). In order to investigate the environmental impacts of hydrogen comprehensively and completely, life cycle assessment, also called "life cycle environmental assessment", which can measure the life cycle environmental impacts of a product/process, was widely used for studying the environmental performances of hydrogen "from cradle to grave". Koroneos *et al*. (2004) employed life cycle assessment to investigate the environmental impacts of hydrogen based on natural gas steam reforming and production from renewable energy sources. Cetinkaya *et al*. (2012) used life cycle assessment to compare the greenhouse gas emissions and consumed energy of five pathways for hydrogen production, including steam reforming of natural gas, coal gasification, water electrolysis via wind and solar electrolysis, and thermochemical water splitting with a Cu–Cl cycle. Dufour *et al*. (2012) used life cycle assessment to compare different alternatives for hydrogen production from renewable and fossil sources, i.e. water photo-splitting, methane steam reforming with CCS, electrolysis with different electricity sources, solar two-step thermochemical cycles, and auto-maintained methane decomposition with different lay-outs. All these methods can effectively quantify the environmental impacts (i.e. global warming potential and acidification potential) of various hydrogen production pathways, but it is still difficult for the decision-makers/stakeholders to determine the most environmental-friendly scenario among multiple alternatives for hydrogen production. For instance, an alternative for hydrogen production perform better with respect to an indication over another alternative, but it may perform worse on another indicator. Weighting in life cycle assessment to aggregate the multiple aspects of environmental impacts into a general index is the most widely used way to address this (Ren *et al*., 2015c). However, life cycle assessment can merely investigate the environmental impacts of different alternative hydrogen production pathways, and the economic performances and social influences cannot be studied.

In order to consider the three pillars of sustainability (economic, environmental and social aspects) simultaneously, LCSA by integrating LCA, LCC, and SLCA should be used to investigate the environmental, economic, and social performances of different hydrogen production pathways, and the decision-making matrix can be determined after this. The key issue for sustainability ranking of different hydrogen production pathways is a multi-criteria decision making problem, including weights determination and alternatives prioritization. There are three severe challenges in this life cycle sustainability ranking framework, including (1) data collection: some hydrogen production technologies are new emerging processes, it is usually difficult to obtain the exact data of the alternatives with to the criteria in LCSA; (2) poor assumption: it is usually assumed that all the criteria in LCSA are independent and there is on relationship among them when determining the weights of these criteria in LCSA; (3) inaccurate decision making: the traditional multi-criteria decision making method cannot effectively prioritize the alternative hydrogen production pathways under the conditions of lacking exact data.

There are many studies by integrating life cycle tools and multi-criteria decision making methods for selecting the best industrial process among multiple alternatives (Hermann *et al*., 2007; Myllyviita *et al*., 2012; Rabl and Holland, 2008). However, the previous studies focusing on the combinations life cycle tools and multi-criteria decision making methods can only help the decision-makers/stakeholders to learn the life cycle environmental or sustainability performances and assistant them to select the most environmental-friendly or the most sustainable hydrogen production pathway under the condition that all the data can obtained exactly and accurately. In other words, these methods cannot achieve life cycle sustainability ranking under uncertainty conditions-if the data are not crisp numbers, because there are still two weak points in these multi-criteria decision making methods:

(1) The lack of considering various uncertainties: all the data used in LCA or LCSA were assumed to be crisp numbers. Accordingly, the data used in multi-criteria decision making were also crisp numbers, and various uncertainty factors were neglected. Actually, there are usually various uncertainties in life cycle sustainability ranking due to the lack of information and knowledge as well as the variations of data caused by external influences, but it lacks the multi-criteria decision making methods for ranking the alternative hydrogen production pathways under uncertainties;

(2) The lack of considering the independences and interactions among the criteria in multi-criteria decision making: as for the weights of the criteria determined in LCA or LCSA, the users usually neglect to interdependences and interactions among the criteria when calculating their weights using AHP and various modified AHP (i.e. fuzzy AHP and grey AHP) methods in the previous studies.

In order to resolve the above-mentioned two academic gaps, a life cycle sustainability ranking formwork has been developed for ranking hydrogen production pathways in life cycle perspective under uncertainty conditions, the multi-criteria decision making method has been extended to uncertainty conditions, and an interval multi-criteria decision making method for addressing uncertainties has been developed in this study for ranking the alternative processes/products after LCSA, and a novel weighting method which can incorporate the interdependences and interactions among the criteria for sustainability assessment was developed to determine the relative weights (relative importance) of these criteria. More specifically, this study has two main innovations:

(1)Developing an interval evaluation based on distance from average solution method for ranking the alternative processes/products in life cycle perspective under uncertainty conditions, and all the data used in the decision-making matrix are interval numbers rather than crisp numbers-the uncertainty factors have been incorporated in decision-making;

(2) Developing an improved decision-making trial and evaluation laboratory method which can incorporate the interdependences and interactions among the criteria in LCSA for calculating the weights of these criteria.

Besides the introduction section, the remainder parts of this study have been organized as follows: a comprehensive literature review of the weighting method in LCA and the combinations of multi-criteria decision making methods and life cycle tools was presented in section 2; the methods used in this study including the weighting method and the improved multi-criteria decision making method were presented in section 3; an illustrative case has been studied in section 4; the results have been discussed through sensitivity analysis and validation in section 5; and finally, this study has been concluded in section 6.

2. Literature review

Life cycle assessment generates the data with respect to different environmental impact categories, and it is difficult for the users to judge which the best alternative is among multiple options. As mentioned above, weighting method used in life cycle assessment which can aggregate the multiple categories of environmental impacts into a general index is the most widely used way to help the users to identify the best alternative is. Within LCA, weighting is an optional step and is performed after characterisation or normalisation in order to weight against each other the results of the different environmental categories analysed (Ahlroth, 2014; Ahlroth *et al*., 2011; Myllyviita *et al*., 2014). The application of weighting arises in situations where it is difficult to decide that one option is environmentally preferable than another and leads to a single score, which can seem a reduction of complexity but actually is the adding of new information (Bengtsson and Steen, 2000). The decision-makers usually have to face this situation in life cycle assessment of hydrogen production methods.

Several issues have been debated over the past years about the necessity and the modality of weighting within life cycle assessment procedures. Finnveden (1997) raised three important questions about the necessity of weighing and the possibility to give priority to some aspects, the methodological approach to use and finally the weighting factors to be chosen. He also discussed that the weighting method may be influenced by ideological and ethical standpoints, for instance view on the society, on nature and ethical concepts. Other questions raised in the literature regard the extent of utilisation of valuation and weighting methods, how and for what purpose to use these, and finally what methods and input data to utilise for weighting (Ahlroth *et al*., 2011). Other important issues regard where weighting has to be applied in the cause-effect chain, the type of values and preferences and how to measure these (Huppes *et al*., 2012). Huppes *et al*. (2012) developed a taxonomy of weighting approaches, where the preference based weights can be subdivided into individual preferences and collective preferences, which are subdivided in revealed and stated preferences. The methods for weighting can be further classified as monetary methods and non-monetary methods (Finnveden *et al*., 2009). Among the monetary methods, we can find willingness to pay techniques, which represent an individual stated preference (Huppes *et al*., 2012), and among the non-monetary methods we can find distance-to-target and panel weighting methods (Ahlroth *et al*., 2011), which are based on collective stated preference. The panel methods include specific methods using expert or stakeholders' assessments and multi-criteria analyses (Ahlroth *et al*., 2011), which allow solving problems with multiple objective and quantifying trade-off among contributions (Ahlroth, 2014).

Within LCA typical weighting sets include ReCiPe Endpoint (Goedkoop *et al*., 2009); Impact 2002+ (Jolliet *et al*., 2003), ILCD 2011 Midpoint + (EC-JRC, 2011), EPS 2000 (Steen, 1999); EDIP 2003 (Laurent *et al*., 2011) and Ecological Scarcity 2013 (Frischknecht and Bϋsser Knöpfel, 2013). Beyond these weighting sets, several authors mainly used the specific distance-to-target and panel methods to weight results of an impact assessment (Ahlroth, 2014). For instance, Lin *et al*. (2005) applied a distance-to-target weighting based on Chinese environmental policy over the years 1995-2005 and Castellani *et al*. (2016) developed a distance-to-target weighting method for Europe. Sappälä and Hämäläinen (2001) and Güereca *et al*. (2007) discussed the application of distance-to-target method with multi-attribute value theory. Itsubo *et al*. (2004) discussed weighting through the application of conjoint analysis presenting questionnaires to 400 persons and using the LIME method; they also developed a statistical analysis for the elaboration of Japanese average weighting factors through LIME 2 (Itsubo et al., 2012). Finnveden *et al*. (2006) developed an approach based on the use of ecotaxes and fees in Sweden. Cortés-Borda *et al*. (2013) analysed how to translate decision makers' preferences into weights via linear programming for the design of hydrogen infrastructure. Ji and Hong (2016) studied how integrating various environmental impacts using both a panel method and monetary evaluation. Several other authors made use of panel methods and utilised multi-criteria decision analyses (MCDA). For instance Myllyviita *et al*. (2014) organised a panel of Nordic LCA expert and used different MCDA weight techniques, such as SWING, Simple Multi-Attribute Rating Technique (SMART) and Analytic Hierarchy Process (AHP); Prado-Lopez *et al*. (2014) used a stochastic multi-attribute analysis for life-cycle impact assessment (SMAA-LCIA) to analyse different laundry detergents. Agarski *et al*. (2016) applied a multi-criteria fuzzy logic methodology to four waste treatment processes, Väisänen *et al.* (2016) and von Doderer and Kleynhans (2014) used AHP for decision-making about a sustainable local distributed energy system in Finland and for determining the most sustainable lignocellulosic bioenergy system, respectively. Kolosz *et al*. (2013) discussed AHP by the use of Dempster-Shafer theory applied to intelligent transport systems. The need to weight the results in a comprehensive way and try to make easier to compare different alternatives is not only a prerogative of LCA, other tools indeed can envisage the utilisation of weighting methods (Ahlroth *et al*., 2011).

According to the above-mentioned literature reviews, the combination of life cycle assessment and multi-criteria decision-making can effectively help the stakeholders/decision-makers select the most environmental-friendly pathway way for hydrogen production among multiple. However, life cycle assessment cannot incorporate the economic and social performances of a product/process. Sustainability assessment emphasizes the evaluation of economic performances, environmental impacts and social effects simultaneously. Life cycle sustainability assessment (LCSA) which combines LCA, life cycle costing (LCC) and social life cycle assessment (SLCA) can achieve sustainability assessment in life cycle perspective (Kloepffer, 2008; Heijungs *et al*., 2010). Moreover, the indicators in technological and political aspects were also incorporated for sustainability assessment recently (Ren and Lützen, 2017). Indeed, with reference to SLCA (Social Life Cycle Assessment), Jørgensen *et al*. (2009) highlighted that, accordingly to the opinion of some interviewed companies; weighting of social impacts may be performed in relation to the comparison of products. Parent *et al*. (2010) discussed the possibility to aggregate the indicators calculated following a weighting system representing the international Performance Reference Points. Wang *et al*. (2016) analysed the social life cycle impact assessment methods based on the UNEP/SETAC Guidelines developed by other authors and proposed the consistent fuzzy preference relations (CFPR) method to determine the relative weights of subcategories and indicators analysing the social impacts in the Taiwanese electronics industry. However, focussing on Life Cycle Costing (LCC) we can find that no weighting factors are used for the different costs and the users decide which costs are relevant (Ahlroth *et al*., 2011; Ahlroth, 2014). Rather the application of weighting arises in situations where it is not possible to decide unambiguously that one option is preferable than another from both an environmental and economic point of view, as occurs when both economic and environmental evaluations are performed. Multi-criteria decision making methods were used for selecting the best alternative among multiple options after using the life cycle tools to collect the data of the options with respect to the criteria in environmental, economic and social aspects. For instance, De Feo and Malvano (2012) elaborated technical and economic analysis and LCA of a municipal solid waste kerbside collection and used the Simple Additive Weighting method to compare the alternatives; Dong *et al*. (2014) applied LCA and LCC to different municipal solid waste management systems using a multi-criteria decision making method calculation procedure of combined TOPSIS and AHP. As mentioned in the introduction section, the previous studies about the combinations of life cycle tools and multi-criteria decision making methods cannot address the situations with data uncertainties. Therefore, a life cycle sustainability ranking framework for prioritizing the alternative hydrogen production pathways under data uncertainties was developed in section 3.

3. Methods

The framework of life cycle sustainability ranking was firstly presented in section 3.1; then, the improved DEMATEL (decision-making trial and evaluation laboratory) method for determining the weights of the criteria for sustainability assessment was presented in section 3.2; finally, the interval multi-criteria decision making method was developed for sustainability ranking of hydrogen production pathways in life cycle perspective in section 3.3.

3.1 Life cycle sustainability ranking framework

The framework of life cycle sustainability ranking of hydrogen production pathways was presented in Figure 1. In this framework, LCA, LCC, and SLCA were employed to obtain the data of the alternative hydrogen production pathways with respect to the criteria in environmental, economic and social aspects, respectively. According to the results of LCA, the data of the alternative hydrogen production pathways with respect to the criteria in environmental aspect (i.e. climate change, human toxicity, particulate matter formulation, land occupation, and fossil depletion) can be determined (Niero *et al*., 2014). According to the results of LCC, the the data of the alternative hydrogen production pathways with respect to the criteria in economic aspect such as production cost, life cycle cost, net present value (NPV), and internal return ratio (IRR) can be determined (Ren *et al*., 2015c). SLCA can be used to determine the data with respect to the criteria in social aspect, i.e. social acceptability, added job, health and safety, fair wage, and social benefit and security (Chen and Holden, 2017; Ren *et al.*, 2015c). It is worth pointing out that the users of the framework of life cycle sustainability ranking developed in this study can choose parts of the criteria or added more criteria for measuring each of the three pillars of sustainability according to the actual conditions and their special preferences (Ren *et al.*, 2016). For instance, the users can different international standards (i.e. ISO 14040 and ISO 14044) and different LCA methodologies (i.e. midpoint approach methodologies, endpoint approach methodologies, and combined midpoint and endpoint approach) for life cycle assessment, and the environmental impact categories may be different when adopting different LCA methodologies (Finkbeiner *et al.*, 2006). In other words, the users can select the suitable criteria for life cycle sustainability ranking of hydrogen production pathways. Besides the criteria in environmental, economic and social aspect, Ren *et al.* (2016) pointed out that the criteria in technological aspect should also be incorporated in sustainability assessment or measurement, because these criteria can effectively influence the criteria in the three pillars of sustainability. Accordingly, production cost (C_1) in economic pillar, global warming potential (C_2) and acidification potential (C_3) in environmental pillar, social acceptability (C_4) in social pillar, and maturity (C_5), energy efficiency (C_6) and exergy efficiency (C_7) in technological aspect were employed for life cycle sustainability ranking of alternative hydrogen production pathways.

The decision-making matrix which consists of the data of the alternative hydrogen production pathways with respect to the criteria in environmental, economic and social can be then determined. An improved DEMATEL method which can consider the interdependences and interactions among the criteria in environmental, economic and social aspects for sustainability assessment was developed to determine the weights of the criteria used in the decision-making. Different from the traditional method for determining the initial direct-influenced matrix, the logarithmic fuzzy preference programming based fuzzy analytic hierarchy process (LFPPFAHP) which can calculate the relative effects of several criteria on a certain criterion was used to determine the initial direct-influenced matrix. An improved Evaluation based on Distance from Average Solution method which can address the decision-making matrix composed by interval numbers was developed for ranking the hydrogen production pathway.

All in all, the developed life cycle sustainability ranking framework can be divided into three stages, and they are:

Stage 1: Determining the decision-making matrix for sustainability ranking. LCA, LCC and SLCA can be used to collect the data of the alternative hydrogen production pathways with respect to the criteria in environmental, economic and social aspects, respectively. Different from the traditional LCA, LCC, and SLCA, interval numbers instead of crisp numbers which can address data uncertainties can be used to determine the decision-making matrix composed by the interval numbers.

Stage 2: Determining the weights of the criteria for sustainability ranking. The improved DEMATEL method can be to determine the weights of the criteria used in multi-criteria decision making methods.

Stage 3: Ranking the hydrogen production pathways. The improved Evaluation based on Distance from Average Solution method can be used to rank the hydrogen production pathways.

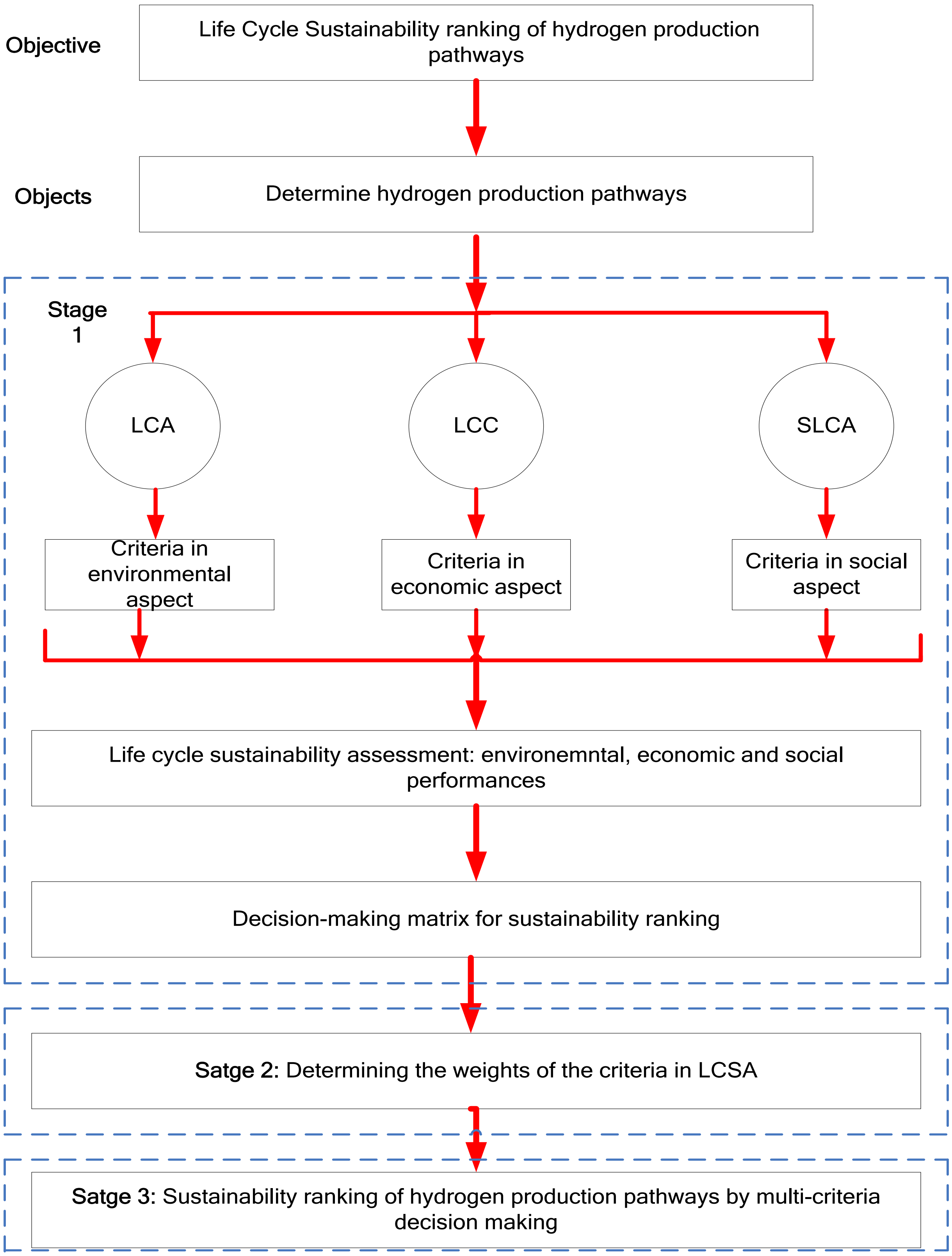

Figure 1: The life cycle sustainability ranking framework for prioritizing the hydrogen production pathways

3.2 Weights determination by the improved DEMATEL

Analytic hierarchy process (AHP) and various weighting methods derived from AHP for weights determination cannot incorporate the interdependences and interactions among these criteria (Ren *et al.*, 2014; Ren *et al.*, 2017). Therefore, a novel weighting method which can incorporate the interdependences and interactions among these criteria has been developed in this study. In the traditional DEMATEL method, the users usually used the integer score from 0 to 4 which correspond to “No influence”, “Low influence ”, “Medium influence”, “High influence ”, and “Very high influence”, respectively, to depict the relative influence of an element over another (Ren *et al.*, 2013). However, it is usually difficult for the users to accurately depict the relative influences of a number of elements on some certain elements. In order to accurately describe the relative influences of a number of elements on some certain elements, the logarithmic fuzzy preference programming based fuzzy analytic hierarchy process was combined with the thoughts of the traditional DEMATEL method to develop an improved DEMATEL for determining the weight of the indicators for life cycle sustainability ranking of the alternative hydrogen production methods.

The improved DEMATEL consists of four main steps based on the thoughts of the traditional DEMATEL method (Fontela and Gabus, 1976; Wu, 2012):

Step 1: Invite the experts to use the logarithmic fuzzy preference programming based fuzzy analytic hierarchy process (LFPPFAHP) to determine the initial direct-influenced matrix;

Step 2: Determine the normalized initial direct-influenced matrix;

Step 3: Calculate the total relation matrix;

Step 4: Determine the weights of the criteria.

The above mentioned four steps have been specified as follows:

Step 1: Invite the experts to use the logarithmic fuzzy preference programming based fuzzy analytic hierarchy process (LFPPFAHP) (Wang and Chin, 2011) to determine the initial direct-influenced matrix. This step aims at determining the relative influence of each indicator on all the other indicators.

Assuming that there are n categories, denotes the *k*-th category $\left(k=1,2,\cdots,n\right)$ by C_k, and there are also several elements in each category, denotes the n_k indicators by e_{k1}, e_{k2},……, e_{kn_k} . The initial direct-influenced matrix which consists of the information about the relative effects of each indicator on the other indicators can be denoted by Eq.1. The matrix segment, B_{ij}, represents the relative effects of the *i*-th category on the *j*-th category. In other words, it was composed by the relative effects of the indicators in the *i*-th category on the indicators in the *j*-th category. The elements in each column of B_{ij} is a local priority vector which represent the elements in the *i*-th category on the elements in *j*-th category and can be obtained by the logarithmic fuzzy preference programming based fuzzy analytic hierarchy process after determining the corresponding pairwise comparison matrix. LFPPFAHP has been employed to determine the elements of each column in matrix segment B_{ij} in this study.

$$
\begin{array}{cc|ccccc}
 & & C_1 & \cdots & C_k & \cdots & C_N \\
 & & e_{11}\cdots e_{1n_1} & \cdots & e_{k1}\cdots e_{kn_k} & \cdots & e_{n1}\cdots e_{nn_N} \\
\hline
C_1 & \begin{matrix} e_{11} \\ \vdots \\ e_{1n_1} \end{matrix} & B_{11} & \cdots & B_{1k} & \cdots & B_{1N} \\
\vdots & & \vdots & \vdots & \vdots & \vdots & \vdots \\
C_k & \begin{matrix} e_{k1} \\ \vdots \\ e_{kn_1} \end{matrix} & B_{k1} & \cdots & B_{kk} & \cdots & B_{kN} \\
\vdots & & \vdots & \vdots & \ddots & \vdots & \vdots \\
C_N & \begin{matrix} e_{n1} \\ \vdots \\ e_{nn_N} \end{matrix} & B_{N1} & \cdots & B_{Nk} & \cdots & B_{NN}
\end{array}
\qquad (1)
$$

The three steps of LFPPFAHP method developed by Wang and Chin (2011) were presetned as follows:

Sub-step 1: Determine the comparison matrix.

Assuming that there are s indicators (t=1,2,…, s) to be studied for comparing their relative influences on an element. The pair-wise comparison matrix can be firstly determined by the users by using the linguistic variables, including "Equal importance (E)" , "Weak importance (W)", "Moderate importance (M)", "Fairly strong importance (FS)", "Very strong importance (VS)", "Absolute importance (A)" which correspond to (1,1,1) , (2/3,1,3/2), (1,3/2,2), (3/2,2,5/2), (2,5/2,3) and (5/2,3,7/2), respectively (Tseng et al., 2009). It is worth pointing out that their reciprocals denoted by RW, RM, RFS, RVS, RA which correspond to (2/3,1,3/2), (1/2,2/3,1), (2/5,1/2,2/3) and (1/3,2/5,1/2), (2/7,1/3,2/5), respectively, were also used to determine the comparison matrix.

Denotes the t-th criterion by C_t, the comparison matrix can be determined by comparing the relative influences of each pair of indicators on some certain indicators, as presented in Eqs.2-3.

$$\tilde{M} = \begin{array}{c|cccc} & e_1 & e_2 & \cdots & e_s \\ e_1 & (1,1,1) & \tilde{m}_{12} & \cdots & \tilde{m}_{1s} \\ e_2 & \tilde{m}_{21} & (1,1,1) & \cdots & \tilde{m}_{2s} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e_s & \tilde{m}_{s1} & \tilde{m}_{s2} & & (1,1,1) \end{array} \tag{2}$$

$$\tilde{m}_{kt} = \frac{1}{\tilde{m}_{tk}} = \left(\frac{1}{m_{tk}^u}, \frac{1}{m_{tk}^m}, \frac{1}{m_{tk}^l} \right) \tag{3}$$

where $\tilde{M}$ is the comparison matrix composed by using the triangular fuzzy numbers, $\tilde{m}_{tk} = \left(m_{tk}^l, m_{tk}^m, m_{tk}^u \right)$ represents the relative influence of the t-th indicator on an indicator over that of the k-th indicator on that indicator, and m_{tk}^l, m_{tk}^m and m_{tk}^u are the three elements of the triangular fuzzy number $\tilde{m}_{tk}$.

Sub-step 2: Determine the natural logarithm of the weight of each indicator which represents the relative influences of each indicator by using the logarithmic fuzzy preference programming (LFPP)-based nonlinear priority model (Wang and Chin, 2011). The natural logarithm of the weight of each indicator can be determined by solving programming (4).

$$\begin{aligned}
&Minimize\ J = (1-\lambda)^2 + M\sum_{t=1}^{s-1}\sum_{k=t+1}^{s}\left(\delta_{tk}^2 + \eta_{tk}^2\right) \\
&x_t - x_k - \lambda\ln\left(m_{tk}^m / m_{tk}^l\right) + \delta_{tk} \ge \ln m_{tk}^l, t = 1,2,\cdots,s-1; k = 1,2,\cdots,s \\
&-x_t + x_k - \lambda\ln\left(m_{tk}^u / m_{tk}^m\right) + \eta_{tk} \ge -\ln m_{tk}^u, t = 1,2,\cdots,n-1; k = 1,2,\cdots,n \\
&\lambda, x_t \ge 0, t = 1,2,\cdots,s \\
&\delta_{tk}, \eta_{tk} \ge 0, t = 1,2,\cdots,s-1; k = t+1,2,\cdots,n
\end{aligned} \tag{4}$$

where $x_t = \ln b_t (t = 1,2,\cdots,s)$, $b_t (t = 1,2,\cdots,s)$ represents the relative influences of the *t*-th criterion on the corresponding criterion, M is a sufficiently large constant set by the users (such as $M = 10^9$), λ represents the minimum membership degree to the logarithm of a triangular fuzzy judgment which can be recognized as an approximate triangular fuzzy number, and $\delta_{ij}, \eta_{ij} \ge 0, i = 1,2,\cdots,n-1; j = 1,2,\cdots,n$ are the assumed nonnegative deviation variables to avoid λ from taking a negative value.

Sub-step 3: Calculate the relative influences of the indicators. The relatvie influece of the *t*-th indicator on the corresponding indicator can be determiend by Eq.5. In a similar way, all the relative influences of the indicators can be determined, as presented in Eq.6.

$$b_t^* = \frac{\exp(x_t^*)}{\sum_{t=1}^{s}\exp(x_t^*)} = \frac{b_t}{\sum_{t=1}^{s} b_t} \tag{5}$$

$$B = \left[b_1^*, b_2^*, \cdots, b_s^*\right] \tag{6}$$

where $b_t^* (t = 1,2,\cdots,s)$ represents the normalized relative influences of the *t*-th criterion on the corresponding criterion, and B is the vector of the relative influences of the s indicators on the corresponding criterion.

Then, the relative influences of the s indicators can be put in the appropriate places of the matrix presented in Eq.1. In a similar way, all the elements in the direct-relation matrix can be determined. The initial direct-relation matrix could then be simplified as:

$$\left[b_{ij}^{*}\right]_{n\times n}=\begin{bmatrix} 0 & b_{12}^{*} & \cdots & b_{1s}^{*} \\ b_{21}^{*} & 0 & \cdots & b_{2s}^{*} \\ \vdots & \vdots & \ddots & \vdots \\ b_{s1}^{*} & b_{s2}^{*} & \cdots & 0 \end{bmatrix} \tag{7}$$

Step 2: Determine the normalized initial direct-influenced matrix (Wu, 2012).

The normalized initial direct-relation matrix D could be obtained by Eq.8.

$$D=\left[d_{tk}\right]_{s\times s}=\frac{B}{\max\left(\max\limits_{1\le i\le s}\sum_{j=1}^{s}b_{ij}^{*},\max\limits_{1\le j\le s}\sum_{i=1}^{s}b_{ij}^{*}\right)} \tag{8}$$

where D is the normalized initial direct-relation matrix, and b_{ij}^{*} and b_{tk}^{*} represents the normalized relative influences of the *i*-th criterion on the *j*-th criterion. $\sum_{j=1}^{s}b_{ij}^{*}$ represents the direct effects of the *i*-th indicator on the other indicators, and $\max\limits_{1\le i\le s}\sum_{j=1}^{s}b_{ij}^{*}$ represents the indicators has the largest influence on other indicators. On the other hand, $\sum_{i=1}^{s}b_{ij}^{*}$ represent the direct influences on the *j*-th indicator affected by the other indicators, and $\max\limits_{1\le j\le s}\sum_{i=1}^{s}b_{ij}^{*}$ represents the indicators which is the most influenced by the other factors.

Step 3: Determine the total relation matrix (Tzeng *et al*., 2007).

The powers of D reflect the indirect influences between each pair of factors. A continuous decrease of the indirect influences of factors along the powers of matrix D, including D^2, D^3,…, D^{∞}. With the increase of the exponent, similar to Markov chain matrix, all in elements in the matrix of the powers of matrix approach to zero. This can guarantee convergent solutions to the matrix inversion. Accordingly, the total relation matrix T could be obtained by Eq.9.

$$T = \left[t_{ij} \right]_{n\times n} = \sum_{i=1}^{\infty} D_i = D(I-D)^{-1} \tag{9}$$

where T represents the total relation matrix, and I represents the identity matrix.

The total direct and indirect effects exerted by the *t*-th indicator, r_t could be determined by Eq.10.

$$r_t = \sum_{k=1}^{s} t_{tk} \tag{10}$$

The total effect including direct and indirect effects received by the *k*-th factor, c_k could be calculated by Eq.11.

$$c_k = \sum_{t=1}^{s} t_{tk} \tag{11}$$

Step 4: Determine the weights of the indicators (Liu *et al.*, 2015).

The weight of each indicator can be determined by Eq.12.

$$\omega_t = \frac{\sqrt{r_t^2 + c_t^2}}{\sum_{t=1}^{s}\sqrt{r_t^2 + c_t^2}} \tag{12}$$

where ω_t represent the weight of the t-*th* indicator.

3.3 Interval multi-criteria decision making method

The traditional Evaluation based on Distance from Average Solution (EDAS) developed by Keshavarz Ghorabaee *et al*. (2015) was extended to interval conditions for addressing uncertainties in this study. For more information of this method, the readers can refer the works of Ghorabaee *et al*. (2017) and Kahraman *et al*. (2017).

Sets

m alternatives: $A_1, A_2, \cdots, A_m$;

n criteria/indicators: $C_1, C_2, \cdots, C_n$;

n weights: $\omega_1, \omega_2, \cdots, \omega_n$.

The interval EDAS developed in this study which can address both crisp and interval data enables the users to rank the alternatives was specified in the following six steps based on the works of Ghorabaee *et al*. (2017) and Kahraman *et al*. (2017):

Step 1: Determine the weights of the evaluation criteria/indicators and the decision-making matrix under uncertainties. The weights of the evaluation criteria/indicators were determined by the improved DEMATEL method which can consider the interdependent and interacted relationships among the evaluation criteria/indicators. The weights of the evaluation criteria/indicators and the decision-making matrix were represented in Eq.13.

$$\begin{array}{cccccc} & C_1 & C_2 & \cdots & C_n \\ A_1 & \begin{bmatrix} z_{11}^- & z_{11}^+ \end{bmatrix} & \begin{bmatrix} z_{12}^- & z_{12}^+ \end{bmatrix} & \cdots & \begin{bmatrix} z_{1n}^- & z_{1n}^+ \end{bmatrix} \\ A_2 & \begin{bmatrix} z_{21}^- & z_{21}^+ \end{bmatrix} & \begin{bmatrix} z_{22}^- & z_{22}^+ \end{bmatrix} & \cdots & \begin{bmatrix} z_{2n}^- & z_{2n}^+ \end{bmatrix} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & \begin{bmatrix} z_{m1}^- & z_{m1}^+ \end{bmatrix} & \begin{bmatrix} z_{m2}^- & z_{m2}^+ \end{bmatrix} & \cdots & \begin{bmatrix} z_{mn}^- & z_{mn}^+ \end{bmatrix} \\ W & \omega_1 & \omega_2 & \cdots & \omega_n \end{array} \tag{13}$$

where W is the weight vector of the n weights, and $\begin{bmatrix} z_{ij}^- & z_{ij}^+ \end{bmatrix}$ represents performance of the *i*-th alternative with respect to the *j*-th indicator.

Step 2: Normalize decision-making matrix. In order to delect the influences caused by the difference in the units of the data in the decision-making matrix, all the data in the decision-making matrix can be normalized by Eq.14 and Eq.15.

As for the positive criteria/indicators:

$$\left[\begin{matrix} f_{ij}^{-} & f_{ij}^{+} \end{matrix}\right]=\left[\begin{matrix} \dfrac{z_{ij}^{-}-\min\limits_{i}\left(z_{ij}^{-}\right)}{\max\limits_{i}\left(z_{ij}^{+}\right)-\min\limits_{i}\left(z_{ij}^{-}\right)} & \dfrac{z_{ij}^{+}-\min\limits_{i}\left(z_{ij}^{-}\right)}{\max\limits_{i}\left(z_{ij}^{+}\right)-\min\limits_{i}\left(z_{ij}^{-}\right)} \end{matrix}\right] \tag{14}$$

As for the negative indicators:

$$\left[\begin{matrix} f_{ij}^{-} & f_{ij}^{+} \end{matrix}\right]=\left[\begin{matrix} \dfrac{\max\limits_{i}\left(z_{ij}^{+}\right)-z_{ij}^{+}}{\max\limits_{i}\left(z_{ij}^{+}\right)-\min\limits_{i}\left(z_{ij}^{-}\right)} & \dfrac{\max\limits_{i}\left(z_{ij}^{+}\right)-z_{ij}^{-}}{\max\limits_{i}\left(z_{ij}^{+}\right)-\min\limits_{i}\left(z_{ij}^{-}\right)} \end{matrix}\right] \tag{15}$$

The normalized decision-making matrix can then be determined, as presented in Eq.16.

$$F=\left|f_{ij}\right|_{m\times n}=\begin{array}{c|cccc} & C_1 & C_2 & \cdots & C_n \\ A_1 & \left[\begin{matrix} f_{11}^{-} & f_{11}^{+} \end{matrix}\right] & \left[\begin{matrix} f_{12}^{-} & f_{12}^{+} \end{matrix}\right] & \cdots & \left[\begin{matrix} f_{1n}^{-} & f_{1n}^{+} \end{matrix}\right] \\ A_2 & \left[\begin{matrix} f_{21}^{-} & f_{21}^{+} \end{matrix}\right] & \left[\begin{matrix} f_{22}^{-} & f_{22}^{+} \end{matrix}\right] & \vdots & \left[\begin{matrix} f_{2n}^{-} & f_{2n}^{+} \end{matrix}\right] \\ \vdots & \vdots & \cdots & \ddots & \vdots \\ A_m & \left[\begin{matrix} f_{m1}^{-} & f_{m1}^{+} \end{matrix}\right] & \left[\begin{matrix} f_{m2}^{-} & f_{m2}^{+} \end{matrix}\right] & \cdots & \left[\begin{matrix} f_{mn}^{-} & f_{mn}^{+} \end{matrix}\right] \end{array} \tag{16}$$

where F is the normalized decision-making matrix, and f_{ij} represents the performances of the *i*-th alternative with respect to the *j*-th indicator, f_{ij}^{-} and f_{ij}^{+} are the lower bound and upper bound of f_{ij}.

Step 3: Determine the average solution (AS) of each indicator which represents the average performance of the alternatives with respect to each indicator. The average solution of the *j*-th criterion can be obtained by Eq.17.

$$AS_j=\frac{\sum_{i=1}^{m}\left(f_{ij}^{-}+f_{ij}^{+}\right)}{2m} \tag{17}$$

where AS_j represents the average solution with respect to the *j*-th criterion, and m is the number of the total alternatives.

Step 4: Calculate the PD (positive distance) and the ND (negative distance) from each alternative to the average solutions with respect to each indicator.

$$\left[PD_{ij}^{-} \quad PD_{ij}^{+}\right]=\left[\frac{\max\left(0,\left(f_{ij}^{-}-AS_j\right)\right)}{AS_j} \quad \frac{\max\left(0,\left(f_{ij}^{+}-AS_j\right)\right)}{AS_j}\right] \tag{18}$$

$$\left[ND_{ij}^{-} \quad ND_{ij}^{+}\right]=\left[\frac{\max\left(0,\left(AS_j-f_{ij}^{+}\right)\right)}{AS_j} \quad \frac{\max\left(0,\left(AS_j-f_{ij}^{-}\right)\right)}{AS_j}\right] \tag{19}$$

where PD_{ij}^{-} and PD_{ij}^{+} represent the lower and upper bounds of the positive distance from the *i*-th alternative to the average solution, respectively. ND_{ij}^{-} and ND_{ij}^{+} represent the lower and upper bounds of the negative distance from the *i*-th alternative to the average solution, respectively.

Step 5: calculate the sum weighted positive distance (SWPD) and the sum weighted negative distance (SWND). The AWPD and SWNP can be determined by Eq.20 and Eq.21, respectively.

$$SWPD_i=\sum_{j=1}^{n}\left[PD_{ij}^{-} \quad PD_{ij}^{+}\right]\times\omega_j=\left[\sum_{j=1}^{n}\omega_j PD_{ij}^{-} \quad \sum_{j=1}^{n}\omega_j PD_{ij}^{+}\right]=\left[SWPD_i^{-} \quad SWPD_i^{+}\right] \tag{20}$$

$$SWND_i=\sum_{j=1}^{n}\left[ND_{ij}^{-} \quad ND_{ij}^{+}\right]\times\omega_j=\left[\sum_{j=1}^{n}\omega_j ND_{ij}^{-} \quad \sum_{j=1}^{n}\omega_j ND_{ij}^{+}\right]=\left[SWND_i^{-} \quad SWND_i^{+}\right] \tag{21}$$

where ω_j represents the weight of the j-th indicator, $SWPD_i$ and $SWND_i$ are the sum weighted positive distance and the sum weighted negative distance of the *i*-th alternative, respectively. $SWPD_i^{-}$ and $SWPD_i^{+}$ are the lower and upper bounds of the sum weighted positive distance of the

i-th alternative, respectively. $SWND_i^-$ and $SWND_i^+$ are the lower and upper bounds of the sum weighted negative distance of the i-th alternative, respectively.

Step 6: Normalize the sum weighted positive distance and the sum weighted negative distance to calculate the normalized sum weighted positive distance (NSWPD) and the normalized sum weighted negative distance (NSWND).

$$\left[NSWPD_i^- \quad NSWPD_i^+\right] = \frac{\left[SWPD_i^- \quad SWPD_i^+\right]}{\max_i\left(SWPD_i^+\right)} \tag{22}$$

$$\left[NSWND_i^- \quad NSWND_i^+\right] = \left[1 - \frac{SWND_i^+}{\max_i\left(SWND_i^+\right)} \quad 1 - \frac{SWND_i^-}{\max_i\left(SWND_i^+\right)}\right] \tag{23}$$

where $NSWPD_i^-$ and $NSWPD_i^+$ are the lower and upper bounds of the normalized sum weighted positive distance of the i-th alternative, respectively. $NSWND_i^-$ and $NSWND_i^+$ are the lower and upper bounds of the normalized sum weighted negative distance of the i-th alternative, respectively.

Step 7: Determine the appraisal scores (APS) of the alternatives. The APS can be determined by Eq.24.

$$\left[APS_i^- \quad APS_i^+\right] = \left[\frac{NSWPD_i^- + NSWND_i^-}{2} \quad \frac{NSWPD_i^+ + NSWND_i^+}{2}\right] \tag{24}$$

where APS_i^- and APS_i^+ represent the lower and upper bounds of the appraisal score of the i-th alternative, respectively.

Step 8: Ranking the appraisal scores and determine the priority order of the alternatives with respect to sustainability.

The probability of $\left[APS_i^- \quad APS_i^+\right]$ which represents the appraisal score of the *i*-th alternative be greater than $\left[APS_j^- \quad APS_j^+\right]$ which represents the appraisal score of the *j*-th alternative can be determined by Eq.25 according to the method for comparing interval numbers developed by Xu and Da (2003).

$$P_{ij} = P\left(\left[APS_i^- \quad APS_i^+\right] \geq \left[APS_j^- \quad APS_j^+\right]\right) = \max\left\{1 - \max\left[\frac{APS_j^+ - APS_i^-}{APS_i^+ - APS_i^- + APS_j^+ - APS_j^-}\right], 0\right\}$$

(25)

where P_{ij} represents the probability of $\left[APS_i^- \quad APS_i^+\right]$ be greater than $\left[APS_j^- \quad APS_j^+\right]$

The probability matrix (see Eq.26) can then be determined by comparing the appraisal scores of each pair of alternatives.

$$P = \begin{vmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & & P_{mm} \end{vmatrix} \tag{26}$$

where P represents the probability matrix

The integrated priorities (IP) of the alternative (Xu and Da, 2003) can then be determined by Eq.27.

$$IP_i = \frac{\sum_{j=1}^{m} P_{ij} + m/2 - 1}{m(m-1)} \tag{27}$$

The alternatives can be ranked according to the integrated priorities, and the greater the value of the integrated priority, the better the alternative will be. While the smaller the value of the integrated priority, the worse the alternative will be.

4. Case study

In order to illustrate the developed model for life cycle sustainability ranking of hydrogen production pathways, four hydrogen production pathways were studied in this section, and they are:

A_1: coal gasification (CG);

A_2: stream reforming of methane (SMR);

A_3: biomass gasification (BG); and

A_4: wind turbine electrolysis (WEL).

All the seven criteria, including production cost (C_1), global warming potential (C_2), acidification potential (C_3), social acceptability (C_4), maturity (C_5), energy efficiency (C_6) and exergy efficiency (C_7), were used to measure the life cycle sustainability performances of the four alternative pathways for hydrogen production in this study.

The developed DEMATEL method was firstly employed to determine the weights of the seven indicators for life cycle sustainability assessment of four alternative pathways for hydrogen production. LFPPFAHP method was used to determine the relative influences of one indicator on another. Taking the relative influences of the other indicators on production cost (C_1) as an example:

Seven top-tier experts of hydrogen production including two professor of chemical engineering, three senior researcher of hydrogen production from renewable, and two postdoctoral fellows of energy engineering were invited to participate in a focus group meeting for establishing the pair-wise comparison matrix by comparing the relative influences of each pair of indicators on C_1. The seven experts held the view that there are only three indicators including maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) can affect the indicator-production cost (C_1), the other four indicators including production cost (C_1), GWP (C_2), AP (C_3), and social acceptability (C_4) do not influence the production cost (C_1), thus, the elements of cell (1,1), cell (1,2), cell (1,3) and cell (1,4) in the first column of the initial direct-influence matrix which represent the influences of C_1,

C_2, C_3 and C_4 on C_1 are 0. In order to determine the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1), the pair-wise comparison matrix was firstly determined by comparing the relative influences of each pair of indicators. For instance, the relative influence of maturity (C_4) on production cost (C_1) comparing with that of energy efficiency (C_5) was recognized as "moderate importance (M)" which corresponds to the fuzzy number (1,3/2,2). In a similar way, all the elements in the comparison matrix can be determined, and the results were presented in Table 1.

Table 1: The comparison matrix for determining the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1)

	C_5	C_6	C_7
Maturity (C_4)	E	M	M
Energy efficiency (C_5)	RM	E	W
exergy Efficiency (C_6)	RM	RW	E
	C_5	C_6	C_7
Maturity (C_4)	(1,1,1)	(1,3/2,2)	(1,3/2,2)
Energy efficiency (C_5)	(1/2,2/3,1)	(1,1,1)	(2/3,1,3/2)
exergy Efficiency (C_6)	(1/2,2/3,1)	(2/3,1,3/2)	(1,1,1)

After determining the pair-wise comparison matrix for determining the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1), the programming for determining the natural logarithm of the weights of three indicator which represents their relative influences on production cost (C_1) can be obtained according to programming (4), and the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1) can be obtained, as presented in Table 2.

Table 2: The results of the programming for determining the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1)

λ	x_1	x_2	x_3	δ_{12}	δ_{13}	δ_{23}	η_{12}	η_{13}	η_{23}
0.0000	1.2346	1.5929	1.2581	0.3584	0.0236	0.3584	0.0000	0.3819	0.0000

Then, the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1) can be determined according to Eqs.5-6, and the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on production cost (C_1) are 0.2895, 0.4142, and 0.2963, respectively. In a similar way, the elements in some other columns can also be determined, and the results were presented in the Appendix.

As for GWP (C_2) and AP (C_3), there are also three indicators (maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7)) influencing this indicator. Note that the relative influences of these three indicators on GWP (C_2) are the same to that of these three indicators on AP (C_3). As for the social acceptability (C_4), the six indicators including production cost (C_1), GWP (C_2), AP (C_3), maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) influence this indicator. As for maturity (C_5) in technological category, there are not any indicators can influence this indicators. Accordingly, the influences of all the indicators on maturity (C_5) are all zero. However, both maturity (C_5) and exergy efficiency (C_7) influences energy efficiency (C_6). Similarly, exergy efficiency (C_7) was also influenced by both maturity (C_5) and energy efficiency (C_6). The initial direct-influenced matrix can then be determined, and the results were presented in Table 3.

Table 3: The initial direct-influenced matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Production cost (C_1)	0	0	0	0.2780	0	0	0
GWP (C_2)	0	0	0	0.1200	0	0	0
AP (C_3)	0	0	0	0.0938	0	0	0
Social acceptability (C_4)	0	0	0	0	0	0	0
Maturity (C_5)	0.2895	0.2230	0.2230	0.1709	0	0.4000	0.3333
Energy efficiency (C_6)	0.4142	0.3195	0.3195	0.2071	0	0	0.6667
Exergy Efficiency (C_7)	0.2963	0.4575	0.4575	0.1303	0	0.6000	0

According to Eq.8, the initial direct-influenced matrix can be firstly normalized (see the Appendix). Subsequently, the total relation matrix can be obtained according to Eq.9. Then, the total direct and indirect effects exerted and received by each indicator can be determined by Eq.10 and Eq.11, respectively. The results were presented in Table 4. After these, the weights of the seven indicators can be obtained by Eq.12, and the results of the weights were also presented in Table 4.

Table 4: The total direct and indirect effects exerted and received by each indicator, and the weights of each indicator

	C_1	C_2	C_3	C_5	C_6	C_7	C_1
r_t	0.1432	0.0618	0.0483	0	1.4644	1.5672	1.5321
c_t	0.7941	0.8215	0.8215	0.8516	0	0.7542	0.7740
ω_t	0.0981	0.1002	0.1000	0.1035	0.1780	0.2114	0.2087

After determining the weights of the seven indicators for sustainability assessment of hydrogen production pathways, the data of the alternatives with respect to the seven indicators were collected. As for the data of the four alternative hydrogen productions methods with respect to the hard indicators (i.e. production cost (C_1), GWP (C_2), AP (C_3), energy efficiency (C_6), and exergy efficiency (C_7)), they were derived from the published works (Pilavachi *et al*., 2009; Acar and Dincer, 2014; Ozbilen *et al*., 2011). As for the data with respect to social acceptability (C_4) and maturity (C_5), they were obtained by using the LFPPFAHP method, and the results were summarized in the Appendix.

After determining the data with respect to the social acceptability, the decision-making matrix can be accordingly determined, and the results were presented in Table 5. It is worth pointing out that the data with respect to social acceptability (C_4) and maturity (C_5) are crisp numbers, while the other data are interval numbers derived from the published works of Pilavachi et al. (2009), Acar and Dincer (2014), and Ozbilen et al. (2011) by altering the original data with ±5% derivations as uncertainties. Therefore, the elements of decision-making matrix are mixed by both interval numbers and crisp numbers.

Table 5: The decision-making matrix

		A_1	A_2	A_3	A_4
Production cost (C_1)	$USD.day^{-1}.kg^{-1}$	[21.25 23.49]	[31.11 34.39]	[22.59 24.97]	[34.91 38.59]
GWP (C_2)	g CO_2 eq. kg^{-1}	[16,150 17,850]	[11,400 12,600]	[2842.4 3141.6]	[1140 1260]
AP (C_3)	g SO_2 eq. kg^{-1}	[29.16 32.22]	[13.79 15.24]	[27.58 30.48]	[2.45 2.71]
Social acceptability (C_4)	/	[0.1457 0.1457]	[0.2003 0.2003]	[0.2754 0.2754]	[0.3787 0.3787]
Maturity (C_5)	/	[0.3429 0.3429]	[0.3429 0.3429]	[0.1820 0.1820]	[0.1321 0.1321]
Energy efficiency (C_6)	/	[0.3325 0.3675]	[0.3563 0.3938]	[0.6175 0.6825]	[0.2945 0.3255]
Exergy Efficiency (C_7)	/	[0.2993 0.3308]	[0.2993 0.3308]	[0.5700 0.6300]	[0.2850 0.3150]

Reference: Pilavachi *et al.*, 2009; Acar and Dincer, 2014; Ozbilen *et al.*, 2011

As for data with respect to the positive criteria/indicators including social acceptability (C_4), maturity (C_5), energy efficiency (C_6) and exergy Efficiency (C_7), they can be normalized by Eq.14. As for data with respect to the negative criteria/indicators including production cost (C_1), GWP (C_2) and AP (C_3), they can be normalized by Eq.15. In a similar way, all the data presented in the decision-making matrix can be normalized (see the Appendix for more details). According to Eq.17, the average solution of each indicator can be determined. The average solutions with respect to the other six criteria were summarized in Table 6.

Table 6: The average solution of each indicator

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Average solution	0.5581	0.5716	0.4373	0.4477	0.5592	0.3267	0.2826

After determining the average solution of each indicator, the matrix of positive distance (PD) and the matrix of negative distance (ND) from each alternative to the average solutions with respect to each indicator can be determined by Eq.18 and Eq.19, respectively. The results were presented in Eq.28.

$$PD = \begin{vmatrix} [0.5606 \quad 0.7918] & [0 \quad 0] & [0.4076 \quad 0.6534] & [0 \quad 0] \\ [0 \quad 0] & [0 \quad 0] & [0.5398 \quad 0.5711] & [0.7368 \quad 0.7494] \\ [0 \quad 0] & [0.3043 \quad 0.4158] & [0 \quad 0] & [1.2668 \quad 1.2867] \\ [0 \quad 0] & [0 \quad 0] & [0.2432 \quad 0.2432] & [1.2334 \quad 1.2334] \\ [0.7883 \quad 0.7883] & [0.7883 \quad 0.7883] & [0 \quad 0] & [0 \quad 0] \\ [0 \quad 0] & [0 \quad 0] & [1.5483 \quad 2.0611] & [0 \quad 0] \\ [0 \quad 0] & [0 \quad 0] & [1.9231 \quad 2.5385] & [0 \quad 0] \end{vmatrix} \qquad (28)$$

The elements in ND can also be determined. The results were presented in Eq.29.

$$PD = \begin{vmatrix} [0 \quad 0] & [0.2274 \quad 0.5659] & [0 \quad 0] & [0.6202 \quad 1.0000] \\ [0.8220 \quad 1.0000] & [0.3247 \quad 0.4504] & [0 \quad 0] & [0 \quad 0] \\ [1.0000 \quad 1.0000] & [0 \quad 0] & [0.6432 \quad 0.8661] & [0 \quad 0] \\ [1.0000 \quad 1.0000] & [0.4766 \quad .47660] & [0 \quad 0] & [0 \quad 0] \\ [0 \quad 0] & [0 \quad 0] & [0.5767 \quad 0.5767] & [1.0000 \quad 1.0000] \\ [0.4241 \quad 0.7002] & [0.2170 \quad 0.5128] & [0 \quad 0] & [0.7554 \quad 1.0000] \\ [0.5308 \quad 0.8538] & [0.5308 \quad 0.8538] & [0 \quad 0] & [0.6923 \quad 1.0000] \end{vmatrix} \qquad (29)$$

After this, the sum weighted positive distance and the sum weighted negative distance can be determined by Eq.20 and Eq.21, respectively. The results were presented in Table 7.

Table 7: The sum weighted positive distance and the sum weighted negative distance

Alternatives	A_1	A_2	A_3	A_4
SWPD	[0.1953 0.2180]	[0.1708 0.1819]	[0.8479 1.1120]	[0.3282 0.3314]
SWND	[0.4627 0.6299]	[0.2608 0.4366]	[0.1670 0.1893]	[0.5430 0.6962]
NSWPD	[0.1756 0.1960]	[0.1536 0.1636]	[0.7625 1.0000]	[0.2951 0.2980]
NSWND	[0.0952 0.3354]	[0.3729 0.6254]	[0.7282 0.7602]	[0 0.2200]
APS	[0.1354 0.2657]	[0.2632 0.3945]	[0.7453 0.8801]	[0.1476 0.2590]

The normalized sum weighted positive distance and the normalized sum weighted negative distance can be determined by Eq.22 and Eq.23, respectively. The results were also presented in Table 7.

The appraisal scores (APS) of the alternatives can then be determined by Eq.24, and the results were also summarized in Table 7. The probability matrix can be determined by Eq.25 and Eq.26， and the elements in the probability matrix were presented in Eq.30.

$$P = \begin{vmatrix} 0.5000 & 0.0095 & 0 & 0.4887 \\ 0.9905 & 0.5000 & 0 & 1.0000 \\ 1.0000 & 1.0000 & 0.5000 & 1.0000 \\ 0.5113 & 0 & 0 & 0.5000 \end{vmatrix} \tag{30}$$

Finally, the integrated priorities of the four alternative pathways for hydrogen production can be determined by Eq.27, and the results were presented in Table 8.

Table 8: the integrated priorities of the four alternative pathways for hydrogen production

Alternatives	A_1	A_2	A_3	A_4
Integrated priorities	0.1665	0.2909	0.3750	0.1676

According to the integrated priorities of the four alternative pathways for hydrogen production, biomass gasification (BG) was recognized as the most sustainable one among these scenarios, stream reforming of methane (SMR) was ranked in the second position, wind turbine electrolysis (WEL) and coal gasification (CG) were recognized as the worst, and their integrated priorities are very close. Therefore, the priority sequence of these four hydrogen production pathways from the most sustainable to the least is BG, SMR, and WEL&CG. BG was also recognized as the most sustainable one by Ren *et al*. (2016). The results were reasonable, BG has the highest exergy efficiency and energy efficiency which have the highest weights in the decision-making, and relatively better economic and environmental performances compared with the other three pathways for hydrogen production.

In this case, some of the data with respect to environmental and economic aspects in life cycle perspective were derived from literatures, and the data with respect social aspect were determined by using the LFPPFAHP method. As for some other cases, the users can use LCA and LCC ot obtained the data of the alternatives with respect to environmental and economic aspects if they cannot find the life cycle environmental and economic performances directly from literatures or technological reports. As for the data of the alternatives with respect to the criteria in social aspect, SLCA can be employed to quantify the values of the alternatives with respect to these criteria, and LFPPFAHP can also be used to determine the relative performances of these alternatives with respect to the criteria which belong to soft criteria in social aspect.

5. Discussion

In order to investigate the effects of the weights of the indicators for life cycle sustainability assessment on the final sustainability ranking of hydrogen production pathways, sensitivity analysis was carried by studying the following nine cases:

Case 0: ranking the four hydrogen production pathways by using the weights determined by the improved DEMATEL

Case 1: Setting equal weights to the seven indicators.

Case 2-8 (i=2, 3 ,…, 8): Setting a dominant weight (0.40) to the (i-1)-*th* indicator and assigning an equal weight (0.10) to the other six indicators.

The results were presented in presented in Figure 2. It is apparent that the change of the weights of the indicators for life cycle sustainability assessment has significant impacts on the final sustainability order of the four alternative pathways for hydrogen production. Meanwhile, it could be concluded that biomass gasification was recognized as the most sustainable in all the nine cases except case 4. Therefore, the result of recognizing BG as the most sustainable one is robust. However, the sustainability ranking of the four alternative pathways for hydrogen production usually changes when altering the weights of the seven indicators for life cycle sustainability assessment of hydrogen production pathways.

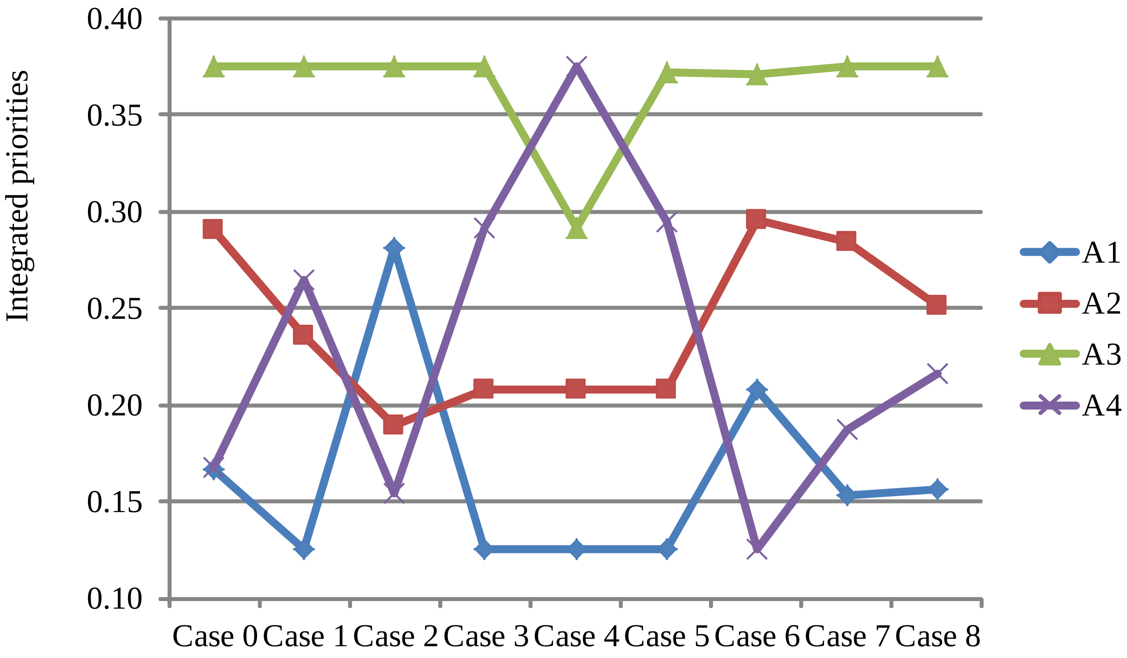

Figure 2: The results of sensitivity analysis

Meanwhile, the interval sum weighted method (ISWM) and interval TOPSIS method (Yue, 2011; Yue, 2012) were also employed to rank the four alternative hydrogen production pathways and to validate the results determined by the interval EDAS based on the weights determined by the improved DEMATEL. After determining the normalized decision-making matrix (see Eq.16), the ISWM has three steps:

Step 1: Determine the weighted normalized decision-making matrix. The weighted normalized decision-making matrix can be determined by Eq.31.

$$D=\omega_j \times \left|f_{ij}\right|_{m\times n} = \begin{array}{cccccc} & C_1 & C_2 & \cdots & C_n & \\ A_1 & \left[\omega_1 f_{11}^- \quad \omega_1 f_{11}^+\right] & \left[\omega_2 f_{12}^- \quad \omega_2 f_{12}^+\right] & \cdots & \left[\omega_n f_{1n}^- \quad \omega_n f_{1n}^+\right] & \\ A_2 & \left[\omega_1 f_{21}^- \quad \omega_1 f_{21}^+\right] & \left[\omega_2 f_{22}^- \quad \omega_2 f_{22}^+\right] & \vdots & \left[\omega_n f_{2n}^- \quad \omega_n f_{2n}^+\right] & = \left|d_{ij}\right|_{m\times n} \\ \vdots & \vdots & \cdots & \ddots & \vdots & \\ A_m & \left[\omega_1 f_{m1}^- \quad \omega_1 f_{m1}^+\right] & \left[\omega_2 f_{m2}^- \quad \omega_2 f_{m2}^+\right] & \cdots & \left[\omega_n f_{mn}^- \quad \omega_n f_{mn}^+\right] & \end{array}$$

(31)

where D is the weighted normalized decision-making matrix, $d_{ij}=\left[d_{ij}^- \quad d_{ij}^+\right]$ represents the element of cell (i, j) in matrix D, and d_{ij}^{-} and d_{ij}^{+} represents the lower and upper bounds of d_{ij}.

Step 2: Determine the sum of each row which represents the integrated priority of each alternative. The integrated priority of the i-*th* alternative can be determined by Eq.32.

$$S_i = \sum_{j=1}^{n} d_{ij} = \sum_{j=1}^{n} \left[d_{ij}^{-} \quad d_{ij}^{+} \right] = \left[\sum_{j=1}^{n} d_{ij}^{-} \quad \sum_{j=1}^{n} d_{ij}^{+} \right] \tag{32}$$

where S_i represents the sum of the i-th row.

Step 3: Ranking the alternative according to Eq.25-27.

As for the procedures of the interval TOPSIS, the readers can refer to Yue (2011, 2012). It is worth pointing out that the sustainability sequence determined by the interval TOPSIS was also based on the weighted normalized decision-making matrix.

Table 9: The comparison of the sustainability ranking determined by the improved EDAS and ISWM

Ranking	1	2	3	4
Ranking by interval EDAS	A_3	A_2	A_1 and A_4	
Ranking by ISWM	A_3	A_4	A_1 and A_2	
Ranking by interval TOPSIS	A_3	A_2	A_1 and A_4	

The comparison of the sustainability ranking determined by the interval EDAS and that determined by ISWM and interval TOPSIS were presented in Table 9. It is apparent that biomass gasification was recognized as the most sustainable all these three multi-criteria decision making methods. Accordingly, it could be concluded that biomass gasification is the most sustainable scenario for hydrogen production among these four alternative pathways.

Meanwhile, the sustainability rankings of these four hydrogen production pathways determined the interval EDAS and the interval TOPSIS are absolutely the same-BG was recognized as most sustainable, followed by SMR, and WEL&CG in the descending order according to their integrated sustainability performances. The integrated priorities of WEL and CG determined by these two methods are also very close. However, the ranking of wind turbine electrolysis determined by these two methods is different from that determined by ISWM. To some extent, it demonstrates that the proposed interval EDAS method is feasible for ranking the alternatives based on the decision-making matrix with interval numbers., and the accuracy of the proposed method is better than the simple additive method (ISWM). Comparing with the interval TOPSIS method, the developed interval EDAS method also has the following two advantages:

(1) the relative integrated priorities of the alternatives were determined through comparing with the average solutions which represent the average level of all the alternatives, and the users have to measure the difference between each alternative with the ideal best solutions as well as that between each alternative with the worst solutions when using the interval TOPSIS;

(2) Each pair of the alternatives will be compared when using the proposed interval EDAS method for ranking the alternatives, and the complete comparisons can effectively the accuracy of the sustainability ranking.

6. Conclusions

This study aims at developing a life cycle sustainability ranking framework for prioritizing the alternative hydrogen production pathways, life cycle sustainability assessment and interval multi-criteria decision making method were combined for prioritizing the alternative hydrogen production pathways in this study. Life cycle assessment, life cycle costing and social life cycle assessment could be employed to obtain the data of the indicators in environmental, economic and social aspects, respectively. In addition, the indicators in technological aspect were also incorporated in the decision-making. An improved DEMATEL method which can consider the interactions and interdependences among the indicators for life cycle sustainability assessment was developed for determining the weights of the indicators. Comparing with the traditional DEMATEL method, the improved DEMATEL can more effectively incorporate the relative effects of the indicators on each indicator. The traditional EDAS method was extended to the interval conditions and the interval EDAS can handle the interval decision-making matrix to achieve decision-making under uncertainties.

All in all, the presented method for sustainability ranking of hydrogen production pathways has the following three advantages:

(1) Life cycle thinking has been incorporated in the multi-criteria decision making for sustainability ranking of hydrogen production pathways;

(2) The improved DEMATEL method can determine the weights of the indicators by considering the independent and interacted relationships among the indicators for sustainability assessment of hydrogen production pathways;

(3) The interval EDAS can rank the alternatives based on the decision-making matrix established by interval numbers for addressing the uncertainties.

Besides the advantages, there is also a weak point which needs to be resolved in future. The proposed multi-criteria decision making method does not allow multiple stakeholders/decision-makers to participate in the process of ranking the alternative hydrogen production pathways. In other words, the developed method cannot incorporate the opinions of different stakeholders/decision-makers. Therefore, the future work of the authors is to develop an interval multi-actor multi-criteria decision making method which can not only address uncertainties, but also can incorporate the opinions of different stakeholders/decision-makers.

Appendix A

Table A1: The pair-wise comparison matrix for determining the relative influences of maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on GWP (C_2) and AP (C_3)

	C_4	C_5	C_6
Maturity (C_4)	E	RM	RFS
Energy efficiency (C_5)	M	E	RM
exergy Efficiency (C_6)	FS	M	E
	C_4	C_5	C_6
Maturity (C_4)	(1,1,1)	(1/2,2/3,1)	(2/5,1/2,2/3)
Energy efficiency (C_5)	(1,3/2,2)	(1,1,1)	(1/2,2/3,1)
exergy Efficiency (C_6)	(3/2,2,5/2)	(1,3/2,2)	(1,1,1)
Relative influences	0.2230	0.3195	0.4575

Table A2: The pair-wise comparison matrix for determining the relative influences of production cost (C_1), GWP (C_2), AP (C_3), maturity (C_5), energy efficiency (C_6), and exergy efficiency (C_7) on GWP (C_2) and Social acceptability (C_4)

	C_1	C_2	C_3	C_5	C_6	C_7
Production cost (C_1)	E	M	FS	VS	FS	VS
GWP (C_2)	RM	E	M	RM	RVS	RM
AP (C_3)	RFS	RM	E	RVS	RFS	RFS
Maturity (C_5)	RVS	M	VS	E	M	FS
Energy efficiency (C_6)	RFS	VS	FS	RM	E	W
Exergy Efficiency (C_7)	RVS	M	FS	RFS	RW	E
	C_1	C_2	C_3	C_5	C_6	C_7
Production cost (C_1)	(1,1,1)	(1,3/2,2)	(3/2,2,5/2)	(2,5/2,3)	(3/2,2,5/2)	(2,5/2,3)
GWP (C_2)	(1/2,2/3,1)	(1,1,1)	(1,3/2,2)	(1/2,2/3,1)	(1/3,2/5,1/2)	(1/2,2/3,1)
AP (C_3)	(2/5,1/2, 2/3)	(1/2,2/3,1)	(1,1,1)	(1/3,2/5,1/2)	(2/5,1/2, 2/3)	(2/5,1/2, 2/3)
Maturity (C_5)	(1/3,2/5,1/2)	(1,3/2,2)	(2,5/2,3)	(1,1,1)	(1,3/2,2)	(3/2,2,5/2)
Energy efficiency (C_6)	(2/5,1/2, 2/3)	(2,5/2,3)	(3/2,2,5/2)	(1/2,2/3,1)	(1,1,1)	(2/3,1,3/2)
Exergy Efficiency (C_7)	(1/3,2/5,1/2)	(1,3/2,2)	(3/2,2,5/2)	(2/5,1/2, 2/3)	(2/3,1,3/2)	(1,1,1)
Relative influences	0.3232	0.2256	0.1575	0.1326	0.0926	0.0685

Table A3: The pair-wise comparison matrix for determining the relative influences of maturity (C_5) and exergy efficiency (C_7) on energy efficiency (C_6)

	C_5	C_7
Maturity (C_5)	E	RM
Exergy efficiency (C_7)	M	E
	C_5	C_7
Maturity (C_5)	(1,1,1)	(1/2,2/3,1)
Exergy efficiency (C_7)	(1,3/2,2)	(1,1,1)
Relative influences	0.4000	0.6000

Table A4: The pair-wise comparison matrix for determining the relative influences of maturity (C_5) and energy efficiency (C_6) on exergy efficiency (C_7)

	C_5	C_6
Maturity (C_5)	E	RFS
Energy efficiency (C_6)	FS	E
	C_5	C_6
Maturity (C_5)	(1,1,1)	(2/5,1/2,2/3)
Energy efficiency (C_6)	(3/2,2,5/2)	(1,1,1)
Relative influences	0.3333	0.6667

Table A5: The normalized direct-influenced matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Production cost (C_1)	0	0	0	0.1432	0	0	0
GWP (C_2)	0	0	0	0.0618	0	0	0
AP (C_3)	0	0	0	0.0483	0	0	0
Social acceptability (C_4)	0	0	0	0	0	0	0
Maturity (C_5)	0.1491	0.1149	0.1149	0.0880	0	0.2060	0.1717
Energy efficiency (C_6)	0.2133	0.1646	0.1646	0.1067	0	0	0.3434
Exergy Efficiency (C_7)	0.1526	0.2356	0.2356	0.0671	0	0.3090	0

Table A6: The pair-wise comparison matrix for determining the relative performances of the four alternatives with respect to social acceptability (C_4)

	A_1	A_2	A_3	A_4
A_1	E	RM	RFS	RVS
A_2	M	E	RM	RFS
A_3	FS	M	E	RM
A_4	VS	FS	M	E
	A_1	A_2	A_3	A_4
A_1	(1,1,1)	(1/2,2/3,1)	(2/5,1/2,2/3)	(1/3,2/5,1/2)
A_2	(1,3/2,2)	(1,1,1)	(1/2,2/3,1)	(2/5,1/2,2/3)
A_3	(3/2,2,5/2)	(1,3/2,2)	(1,1,1)	(1/2,2/3,1)
A_4	(2,5/2,3)	(3/2,2,5/2)	(1,3/2,2)	(1,1,1)
Relative performances	0.1457	0.2003	0.2754	0.3787

Table A7: The pair-wise comparison matrix for determining the relative performances of the four alternatives with respect to maturity (C_5)

	A_1	A_2	A_3	A_4
A_1	E	W	FS	VS
A_2	RE	E	FS	VS
A_3	RFS	RFS	E	M
A_4	RVS	RVS	RM	E
	A_1	A_2	A_3	A_4
A_1	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(2,5/2,3)
A_2	(2/3,1,3/2)	(1,1,1)	(3/2,2,5/2)	(2,5/2,3)
A_3	(2/5,1/2,2/3)	(2/5,1/2,2/3)	(1,1,1)	(1,3/2,2)
A_4	(1/3,2/5,1/2)	(1/3,2/5,1/2)	(1/2,2/3,1)	(1,1,1)
Relative performances	0.3429	0.3429	0.1820	0.1321

Table A8: The normalized decision-making matrix

	A_1	A_2	A_3	A_4
C_1	[0.8710 1.0000]	[0.2423 0.4312]	[0.7856 0.9227]	[0 0.2120]
C_2	[0 0.1017]	[0.3142 0.3860]	[0.8802 0.8981]	[0.9928 1.0000]
C_3	[0 0.1031]	[0.5704 0.6192]	[0.0585 0.1560]	[0.9913 1.0000]
C_4	[0 0]	[0.2343 0.2343]	[0.5567 0.5667]	[1.0000 1.0000]
C_5	[1.0000 1.0000]	[1.0000 1.0000]	[0.2367 0.2367]	[0 0]
C_6	[0.0979 0.1881]	[0.1591 0.2558]	[0.8325 1.0000]	[0 0.0799]
C_7	[0.0413 0.1326]	[0.0413 0.1326]	[0.8261 1.0000]	[0 0.0870]

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